# Constant False Alarm Rate in Fire Detection for MODIS Data

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*Abstract*— **This paper introduces the concept of Constant False Alarm Rate (CFAR) in fire detection for multispectral satellite data. A new algorithm is proposed, based on a technique successfully applied for detection of extended objects in High Resolution SAR images. It compares the pixel under analysis with an adaptive threshold, suitably estimated from the pixels surrounding the one under test, in order to ensure the CFAR property. The proposed approach requires that the background distribution is of Location Scale (LS) type or amenable to such a distribution by a suitable transformation. MODIS data from the 4 $\mu$m channel are considered. A preliminary statistical analysis is performed to verify if the Weibull distribution, compliant with LS representation, can be adopted for background. MODIS cloud and water masking are applied to identify those pixels to be discarded before implementing the statistical analysis. Results of fire detection are presented for different values of the system parameters (censoring depth and false alarm rate) and compared with the algorithm implemented in the NASA-DAAC MOD14.**

## I. Introduction

The MODIS active fire algorithms fall within the suite of terrestrial products and, based on the original work by Kaufman and Justice [1], are continuously updated and modified as, for instance in [2], [3]. These algorithms are based on a combination of tests, using absolute thresholds or adaptive thresholds related to global statistical parameters but are unable to control the probability of false alarm. This property is, on the other hand, highly desirable and widely implemented in radar detection schemes operating under changeable conditions of the surrounding environment. From this context we draw the idea of implementing CFAR techniques suitably modified for detecting thermal anomalies. The approach proposed by [4], [5] will be redesigned in this paper with application to multispectral satellite data acquired from the 4 $\mu$m MODIS channel. The procedure requires more accurate hypotheses about the statistical distribution of the data and, in particular, the satisfaction of the Location–Scale (LS) property. A preliminary statistical analysis is carried out to show that the background data are compatible with a Weibull distribution that becomes of a LS type after a log-transformation. The core of the algorithm consists in setting the adaptive threshold as a function of the estimates of the distributional parameters, as measured from a set of background data while maintaining the CFAR property. Main comparison has been done with enhanced Giglio algorithm [3], showing that our CFAR algorithm achieves similar results. The paper is organized as follows: in the next section, the architecture of the detector is presented with its design issues. Particular attention is given to pre-processing steps including background statistical analysis. The background model is discussed in more details in Section III where the parameters estimation is presented. In Section IV results obtained by processing a set of real data are showed and discussed by comparing them with the Giglio algorithm.

## II. CFAR detection of thermal anomalies

Thermal anomalies can be defined as conditions of unusual (usually high) temperature. Looking at this definition some questions arise such as: How high the temperature values should be for having a thermal anomaly? What are the reliability parameters to account in defining thermal anomalies? Indeed, the observed temperature is a function of many parameters as the sensor spatial resolution, the extension of overheating area inside resolution, influence of the atmosphere. Very high temperatures are reasonably due to thermal anomalies but, as the overall temperature of a cell becomes moderately warm, choosing an adaptive threshold becomes of crucial importance. Even more challenging would be the problem of defining the cost of deciding for anomalies when they are not, or of not detecting them when they are. With this aim, we present here a detection algorithm where the False Alarm Rate is kept Constant (CFAR). Formally, this requires that

$$P_{FA} = \Pr\left\{X > T|H_0\right\} \ , \qquad (1)$$

is constant, where $X$ is a random variable representing the cell under test, $H_0$ denotes the background-only hypothesis and $T$ is the adaptive threshold. Specific solutions to this problem have been found when the data set belongs to some families of distributions such as the LS [4] and the Compound Gaussian [6]. Following [5], we consider here the case where the data set, under $H_0$, can be modeled as Weibull random variables previously log-transformed to obtain a distribution of LS type. It has been also demonstrated that CFAR is achieved under a weaker hypotheses of a data set that is not Weibull but, anyway LS, and in the case of not independent samples.

### A. Scheme of the CFAR detector

Leaving the formal proofs (the interested reader may follow references [4], [5] for a deeper insight), we report here the main steps of the algorithm, Figure 1. From the image under test, a reference window, that is a set of $N$ samples, is taken and the corresponding data, sorted in ascending order and censored, are organized into a vector form. The operation, denoted as *censoring* is here used to ensure protection against

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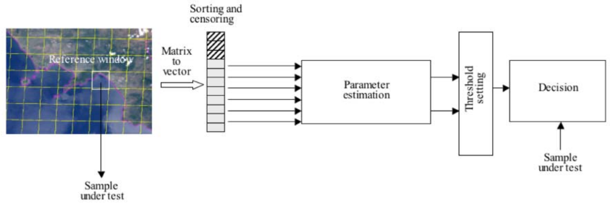


Fig. 1. Scheme of the CFAR detector.

self-masking effects due to the presence of extended thermal anomalies inside the reference window. The last $r$ samples are discarded because they may contain fire pixels with higher probability and the other $N-r$ samples are used for estimating the distributional parameters.

To proceed further in the definition of the processing stages, we have an estimation block where the parameters of the LS distribution are estimated. This is a critical point since only equivariant estimators ensure that the CFAR property is maintained [4] and not all estimators present the same properties in terms of efficiency or computational complexity [7]. We considered Best Linear Unbiased Estimators (BLUE) which, achieve the minimum variance and are equivariant. The minimization of the variance with the constraint of unbiasedness leads to the estimators of the location and scale parameters [8]

$$\begin{pmatrix} \widehat{\theta}_L \\ \widehat{\theta}_S \end{pmatrix} = \left(\boldsymbol{D}^T \boldsymbol{C}_0^{-1} \boldsymbol{D}\right)^{-1} \boldsymbol{D}^T \boldsymbol{C}_0^{-1} \boldsymbol{Y} \tag{2}$$

where $\boldsymbol{Y}$ is the vector of ranked and censored data, $\boldsymbol{D} = (\boldsymbol{1}\ \boldsymbol{\mu}_0)$ and $\boldsymbol{\mu}_0$ and $\boldsymbol{C}_0$ are the mean vector and the covariance matrix of the standardized ordered and censored statistics, i.e. having zero location and unit scale parameters [5]. Finally, the adaptive threshold is evaluated as

$$T = \widehat{\theta}_S(\boldsymbol{Y})\gamma + \widehat{\theta}_L(\boldsymbol{Y}) \tag{3}$$

where $\gamma$ is a constant value, the so called threshold multiplier, chosen according to the design value of the probability of false alarm $P_{FA}$.

### *B. Selection of the threshold multiplier*

The threshold multiplier is evaluated via Monte Carlo simulation by generating $M$ realizations of the test statistic $(Y - \widehat{\theta}_L)/\widehat{\theta}_S$ and evaluating the $(1 - P_{FA})$–quantile from the empirical Cumulative Distibution Function (CDF). The dimension of the reference set for the estimation of the parameters is ruled by the homogeneity level of the data under test and by the maximum dimension of the thermal anomalies, with the understanding that a large sample set allows better estimate of the background parameters and, hence, higher detection probability.

## III. Statistical validation

Statistical analysis is made on MODIS channel 21 at 4 $\mu$m to verify the assumption that the background distribution is compatible with a three–parameter Weibull CDF

$$F_X(x) = 1 - \exp\left[-\left(\frac{x-\delta}{\alpha}\right)^{\beta}\right] \quad \alpha, \beta, \delta > 0 \ \ , x \geq \delta \tag{4}$$

where $\alpha$, $\beta$ and $\delta$ are the scale, the shape and the location parameters, respectively. The usual way for verifying if a set of data is compatible with a design distribution $F_X(x)$ is the Kolmogorov Smirnov (KS) test [9]. The KS test requires that the samples under test are independent, but this is generally hard to achieve in remote sensed data that are usually non Gaussian and correlated. This is also the case of MODIS data [10] where the received radiances are intrinsically non negative (and thus non Gaussian) and, at least for the thermal infrared channels, the correlation length is of the order of several Km. An alternative procedure is to resort to a distributional distance between the theoretic and the empirical CDFs. Our aim would be to make a joint ML estimation of $\alpha$, $\beta$ and $\delta$, but the solution is numerically cumbersome and the existence of local minima may cause the final result to be different from the global one [11]. In our implementation, we have introduced an iterative procedure where the location parameter is estimated using a linear extrapolation and the shape and scale parameters are estimated via a simpler two-parameter ML algorithm. Thus, the following steps have been implemented

*Inizialization*

1) Evaluation of the empirical CDF $\widehat{F}_X(x)$ from the sample set, i.e. the couples $(x_i, y_i),\ i = 1, \cdots N$ ;
2) evaluation of $\widehat{\delta}$ at the first iteration as the $x$–intercept of the linearly interpolated empirical CDF;
3) evaluation of the joint ML estimate of $\alpha$ and $\beta$;

*Iterations*

1) coordinates transformation $z_i = \widehat{\alpha}\left[-\ln(1-y_i)\right]^{1/\widehat{\beta}}$ such that the theoretical curve is now the linear function $z = x - \delta$;
2) evaluation of $\widehat{\delta}$ at the $i$–th iteration as the $x$–intercept of the linearly fitted samples $(x_i, z_i)$.
3) evaluation of the joint ML estimate of $\alpha$ and $\beta$ at the $i$–th iteration;

*Stopping condition*

The estimated parameters at the $i$–th and $(i-1)$–th iteration differ for less than a predefined value $\epsilon$. $\square$

The estimation procedure has been applied for data validation in the region of interest and the Cramer-Von Mises distance between distributions has been used as indicator of discrepancy. The distance is evaluated as [9]

$$W^2 = \frac{1}{12N} + \sum_{i=1}^{N} \left(F(X_{(i)}) - \frac{2i-1}{2N}\right)^2 \leq \frac{N}{3} \tag{5}$$

where $X_{(i)}$ is the $i$th order statistic from the set of observations. Results are shown in Figure 2 where the distance $W$ is reported in a color scale over the map of the chosen region. It is interesting to observe that fitting is generally good except for a few windows corresponding to boundaries

between different background textures. This is also shown in Figure 3 where the empirical and the theoretical CDFs are plotted for two situations that we have considered as best (Window A, in Figure 2) and worst (Window B, in Figure 2) cases. We observe that, in boundary regions, the overall samples cluster in two groups as a consequence of the different thermal behavior. The corresponding empirical distribution is expected to be bimodal as appears in Figure 3 for the case of poor fitting.

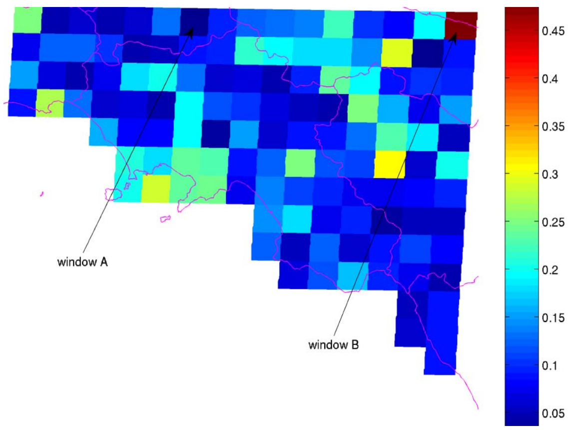


Fig. 2. Color mapped distances between empirical and theoretical CDFs.

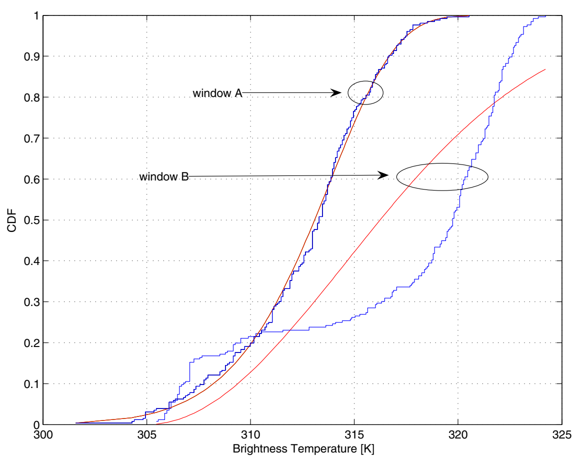


Fig. 3. Comparison between empirical CDFs in the best and worst case.

## IV. Algorithm Description and Results

The fire detection algorithm is organized in the following steps:

- Cloud mask and land/sea mask
- Window selection and sizing
- Logarithm transformation, ranking and censoring of data
- Parameter estimation and threshold setting
- Detection

These steps will be now better illustrated and presented, together with the most significant results obtained from application to a MODIS granule covering the Campania region (Italy), acquired during Terra pass of July 19th 2004 and received at the MARS ground station in Benevento. Data used in the fire detection algorithm are from the $4\mu$m channel, but also auxiliary data from MOD35 product and MOD03 have been used for cloud mask and land/sea mask.

*Cloud mask and land/sea mask* The first step in any fire detection algorithm is the selection of a set of data that are really significant in the detection stage, also excluding data that may induce errors in the whole process. The land/sea mask is thus a necessary step to select land data and is simply obtained from NASA geolocation product MOD03. A more intricate problem is the cloud rejection. In the present algorithm the cloud mask product MOD35 is used for locating cloud pixels that should be rejected in the following steps of the algorithm but, in order to save those data that, flagged as "cloud", may be due to fire smokes, we have introduced a check on bit 8 in the cloud mask, indicating the possible presence of aerosol [12].

*Window selection and sizing* The CFAR detection algorithm requires the estimation of the scene parameters from a reasonably (statistically) homogeneous region; the algorithm also requires that the number of data used in the estimation process is kept constant. For the case at hand, a set of 256 samples has been considered reasonable. Due to these contrasting requirements a certain attention should be paid in clustering the data set according to the background characteristics. In this stage we have introduced a simple but effective procedure where, starting from a first division of the whole image into $16 \times 16$ square windows, these regions are progressively enlarged when the valid data in the window are less than 256 until exactly 256 valid pixels are found.

*Logarithmic transformation, ranking and censoring of data* This step is necessary to make the data of brightness temperature at $4\mu$m channel compatible with the hypotheses required by the CFAR algorithm presented in Section II. First, the estimate of the parameter $\delta$ is subtracted from data to obtain a two parameter Weibull distribution. Then, a logarithmic function is applied to transform the Weibull data, as verified through the statistical analysis reported in Section III, into Gumbel data with the desired Location Scale property. Data in each window are then sorted to make possible a censoring operation aimed at discarding a given number of outliers that may correspond to thermal anomalies. The choice of the censoring depth is often based on empirical considerations: a reasonable rule is to discard a number of samples that is approximately equal to the maximum number of fires expected in the observation window. In particular we have considered, as censoring depths, $r = 0, 4, 8$.

*Parameter estimation and threshold setting* Starting from the ranked and possibly censored sample, the parameter estimation and subsequent threshold setting are performed according to the rules described in Section II and in the reference [5]. Some details can be useful about the value of the threshold multiplier $\gamma$ that is related to the desired false alarm probability and to the applied censoring depth. Results from Monte Carlo simulation show that the curves are generally

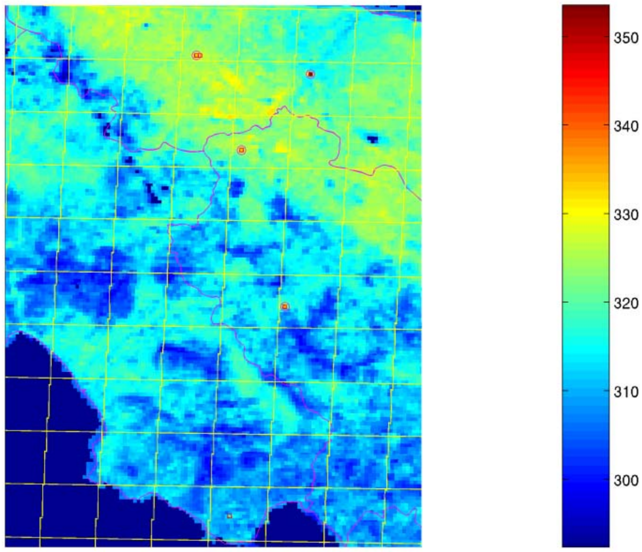


Fig. 4. Results for thermal anomaly detection, colorbar represents $BT_4[K]$

| $r$ | $c_0$ | $c_1$ | $c_2$ |
|---|---|---|---|
| 0 | 0.4651 | -0.6067 | -0.0443 |
| 4 | 0.3772 | -0.6493 | -0.0462 |
| 8 | 0.4051 | -0.6343 | -0.0436 |

TABLE I
COEFFICIENTS FOR EVALUATION OF THE THRESHOLD MULTIPLIER

clustered in the region of high $P_{FA}$ and thus, in this region, the selection of the threshold multiplier is weekly dependent on $r$. Otherwise, in the region of low values of $P_{FA}$, curves are much more influenced by the censoring depth. Results have been interpolated with a polynomial function and the following equation is used in the algorithm for setting the threshold multiplier $\gamma$, according to the desired false alarm probability $P_{FA}$, in the range $-6 \leq \log_{10} P_{FA} \leq -2$:

$$\gamma = c_0 + c_1 \log_{10} P_{FA} + c_2 \left(\log_{10} P_{FA}\right)^2 \qquad (6)$$

where values of coefficient $c_i$ are reported in Table 1 for different values of censoring depth $r$. The thresholds for the final step are obtained from equation (3) for each window.

*Detection* In this final step the temperature data in each window are compared with the corresponding threshold. The detection has been performed for the three values of censoring depth $r = 0, 4, 8$ and results have been compared with results of MOD14 product. Figure 4 shows the fire detection with $r = 8$ where MOD14 fires are marked with a magenta circle and CFAR fires with a small red square. The agreement is evident with only two differences: the fire at (lat 40.0720, lon 15.3686) is detected by the CFAR algorithm but not by MOD14 and in correspondence to the fire at (lat 41.3214, lon 15.5841), detected by both MOD14 and CFAR algorithm, there is another fire in an adjacent pixel detected only by the CFAR algorithm. Finally the results obtained for different censoring depths, not reported here for sake of shortness, show that the fire at (lat 41.0436, lon 15.6751) was not detected with lower values. This is an encouraging result for using the censoring even though the choice of its value is an open issue. For this reason a future work is foreseen with the application of the CFAR algorithm to an area with many forest fires.

## V. CONCLUSIONS

The preliminary validation of the proposed setup has shown that the achieved results are similar to those obtained with the latest NASA–DAAC MOD14 product where, however, the false alarm rate is not guaranteed to be constant. A deeper validation is under development using information from the National Fire Guardianship. A second main improvement is tied to a multiband investigation with a careful attention to account for possible inter–bands correlation. Other areas of investigation regard the following points:

1. *Cloud mask and land/sea mask* A deeper analysis should be focused for a better usage of the bits from cloud mask, with the aim of retaining thin clouds or smoke.
2. *Window selection and sizing* A preliminary data segmentation, based homogeneity criterions, could result in more accurate estimates.
3. *Detection* Performance of the algorithm for different values of the censoring depth should be investigated, possibly having knowledge about the ground truth.

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